

A FRACTAL ANALYSIS OF CT LIVER IMAGES FOR THE DISCRIMINATION OF HEPATIC LESIONS: A COMPARATIVE STUDY

C.-P. A. Sariyanni^{1*}, P. Asvestas¹, G. K. Matsopoulos¹, K. S. Nikita¹, A. S. Nikita², D. Kelekis²

¹ Department of Electrical and Computer Engineering, National Technical University of Athens,
9 Iroon Polytechniou Str., 15773 Zografos, Athens, Greece

² Second Department of Radiology, University of Athens, Medical School, Greece

*Corresponding author: Tel. +30 1 772 2285; Fax: +30 1 772 3557; email: chsari@cc.ece.ntua.gr

Abstract – A quantitative study for the discrimination of different hepatic lesions is presented in this paper. The study is based on the fractal analysis of CT liver images in order to estimate their fractal dimension and to differentiate normal liver parenchyma from hepatocellular carcinoma. Four fractal dimension estimators have been implemented throughout this work; three well-established methods and a novel implementation of a method. Analytically, these methods correspond to the power spectrum method, the box counting method, the morphological fractal estimator and the novel modification of the kth-nearest neighbour method. The Fuzzy C-Means algorithm is finally applied revealing that the k-th nearest neighbour method outperforms the other methods; thus discriminating up to 93% of the normal parenchyma and up to 82% of the hepatocellular carcinoma, correctly.

Keywords – Hepatic lesions, fractal dimension, Brownian motion, box-counting method, morphology, k-nearest neighbour method.

I. INTRODUCTION

Improvements of different medical imaging modalities, such as Computed Tomography (CT), Magnetic Resonance Imaging (MRI) and Ultrasonography have dramatically increased the ability to detect and diagnose liver abnormalities. Nevertheless, biopsy, an invasive technique, remains the most effective for the characterisation of different liver abnormalities. To limit this process, new techniques from the image processing field may be applied to liver images in order to isolate regions of interest and detect liver abnormalities.

Consequently, ultrasound B-scan imaging has become one of the most popular modality to image human abdominal organs such as liver. These images appear as textural ones and various techniques have been applied in order to characterise different tissues to normal or abnormal [1]. Recently, several investigators used MRI and CT in order to evaluate local hepatic lesion of all varieties [2].

Detection of hepatic lesions, using the aforementioned imaging modalities, has been realised from the processing of liver images using different imaging processing techniques, such as texture analysis, grey-scale, shape descriptors, etc. [3]. In particular, texture features based on the Fourier power spectrum, the grey-level different statistics, the grey-level run-length statistics, the spatial grey-level dependent matrices have been used for the liver tissue characterisation [4]. Most of these liver tissue differentiation techniques were based on the analysis of liver images with the emphasis on the problem of classification [4].

Moreover, fractal geometry has received much attention as a useful tool for image analysis [5]. The intensity surface of an image can be considered as a fractal object whose properties are quantified numerically by the use of the fractal dimension. For an image, the fractal dimension is a non-integer number between 2 and 3 and it is a measure of the roughness of its intensity surface. Experiments have demonstrated that the fractal dimension is highly correlated with the human perception of image texture; the rougher the texture appears the larger is the fractal dimension.

The present paper consists of a comparative study of four fractal dimension estimators in order to discriminate different liver lesions. These fractal estimators correspond to three well-known techniques, such as the power spectrum method, the box counting, and the morphological fractal estimator and a novel modification of the kth-nearest neighbour method. These fractal dimension estimators have been implemented and applied to CT liver images to differentiate the following cases: normal parenchyma and hepatocellular carcinoma.

II. METHODOLOGY

The analysis presented in this study was performed in three main steps: (a) Data acquisition, (b) Image pre-processing, and finally, (c) Estimation of the fractal dimension.

A. Data Acquisition

All CT images were captured using a Philips LX CT scanner of the Department of Radiology, at the Eugenidion Hospital - University of Athens, Greece. The scanner consists of a major system of a Local Area Network (LAN) and it is connected to an Agfa Impax MC-300 Medical Gateway, a system that digitises the CT images throughout the Video Spot Imaging (VSI) component. As a result, CT images of 512 x 512 pixels and 256 grey-level distributions were digitised and then driven to a Dicom server, according to the Agfa Protocol IP. Finally, the images were sent to a PC with Windows NT4.0 for further processing.

In the present study, two sets of liver images were finally acquired corresponding to 99 normal parenchymas and 50 hepatocellular carcinomas.

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B. Image Pre-processing

The selected abdominal CT images were then processed in order to extract a particular region of interest (ROIs). These ROIs have been manually drawing by a team of radiologists so as to contain only liver parenchyma (normal or abnormal), with no major blood vessels information. The ROIs were selected along the centre line of each image and were consisted by rectangular areas from 25×25 up to 88×88 pixels size, depending on the liver image.

There were cases where ROIs are difficult to be discriminated from the surrounded liver tissues. Therefore, a contrast enhancement method, such as the histogram equalisation technique [6] was priory performed, in order the ROIs to be successfully identified by the experts. It must be pointed out that the calculation of the fractal dimension estimators were performed on the original data and the enhanced process had been used only for visualisation purposes.

C. Fractal Dimension Estimators

Several methods have been proposed for the estimation of the fractal dimension of liver images. In the present study, the fractal dimension of the various ROIs had been computed throughout four different estimators, regarded as the most representative:

- The Power Spectrum Method (PSM),
- The Box-Counting Method (BCM),
- The Morphological Fractal Estimator (MFE),
- The kth-Nearest Neighbour estimator (K-NN)

The Power Spectrum Method (PSM)

The power spectrum method belongs to the fractional Brownian motion (fBm) methods. The image is assumed to be fBm [7] with parameter:

$$H = 3 - FD \quad (1)$$

with $0 < H < 1$. Then, the power spectrum density of image is given by:

$$P(f_1, f_2) = \frac{k}{\left(\sqrt{f_1^2 + f_2^2}\right)^b} = \frac{k}{\|f\|^b} \quad (2)$$

where k is a positive constant. The exponent b is related with the fractal dimension as follows:

$$b = 2 + 2H = 2(4 - FD) \quad (3)$$

where $2 \leq b \leq 4$. Pentland [7] estimated the exponent b for various directions of the Fourier plane as the slope of the least squares line at the points $(-\log f, \log P(f_1, f_2))$. These estimates were then collapsed into one average measurement, from which the fractal dimension was obtained.

The Box-Counting Method (BCM)

The box-counting method estimates the fractal dimension of a signal (image) as an upper limit of the Hausdorff-Besicovich dimension [5]. The box-counting dimension of a set $S \subset \mathbb{R}^n$ is defined as follows:

$$FD \equiv \lim_{r \rightarrow 0} \frac{\log N(r)}{\log(1/r)} \quad (4)$$

where $N(r)$ denotes the number of n -dimensional cubes, size r , needed to cover set S . The image plane (m, n) is covered by a 3-dimensional grid of cubes for various grid sizes r . The number of cubes, $N(r)$, containing at least one pixel of the image is counted and the fractal dimension is obtained by the slope of the best fitting line at the points $(-\log r, \log N(r))$.

The Morphological Fractal Estimator (MFE)

The morphological fractal estimator belongs to the area measurement methods [8]. The covering methods can measure the Minkowski-Bouligand fractal dimension of a fractal signal by creating multiscale covers round the signal's graph. More precisely these methods are based on the multiscale morphological erosion and dilations.

The dilation and erosion of a function f : $D_f = [0, X_1] \times [0, X_2] \rightarrow \mathbb{R}$ by a structuring element g_ϵ :

$D_{g_\epsilon} \rightarrow \mathbb{R}$ are defined as follow:

$$(f \oplus g_\epsilon)(x_1, x_2) = \sup \{ f(x_1 - s_1, x_2 - s_2) + g(s_1, s_2) / (x_1 - s_1, x_2 - s_2) \in D_f, (s_1, s_2) \in D_{g_\epsilon} \}$$

$$(f \ominus g_\epsilon)(x_1, x_2) = \inf \{ f(x_1 + s_1, x_2 + s_2) - g(s_1, s_2) / (x_1 + s_1, x_2 + s_2) \in D_f, (s_1, s_2) \in D_{g_\epsilon} \}$$

where \oplus denotes dilation and \ominus erosion and $(x_1, x_2) \in D_f$.

Let $f(m_1, m_2)$ be a two-dimensional signal where $(m_1 = 0, 1, \dots, M_1 - 1, m_2 = 0, 1, \dots, M_2 - 1)$. The fractal dimension is then estimated as follows:

STEP 1: Select a convex set structuring element B_d to be a discrete version of a continuous B which satisfies the theorem of [8] and for which the g_ϵ structuring elements are constructed.

STEP 2: For $\epsilon = 1, 2, \dots, \epsilon_{\max}$ the parameters

$$U_\epsilon(m_1, m_2) = (f \oplus g_\epsilon)(m_1, m_2),$$

$$L_\epsilon(m_1, m_2) = (f \ominus g_\epsilon)(m_1, m_2)$$

are recursively calculated:

$$U_{\epsilon=1}(m_1, m_2) = (f \oplus g_{\epsilon=1})(m_1, m_2) \\ = \max_{-1 \leq i, j \leq 1} \{ f(m_1 + i, m_2 + j) + g_{\epsilon=1}(i, j) \}$$

$$U_\epsilon(m_1, m_2) = (U_{\epsilon-1} \oplus g_{\epsilon=1})(m_1, m_2), \epsilon > 1$$

and

$$L_{\varepsilon=1}(m_1, m_2) = (f \ominus g_{\varepsilon=1})(m_1, m_2) \\ = \min_{-1 \leq i, j \leq 1} \{f(m_1 + i, m_2 + j) - g_{\varepsilon=1}(i, j)\}$$

$$L_{\varepsilon}(m_1, m_2) = (L_{\varepsilon-1} \ominus g_{\varepsilon=1})(m_1, m_2), \varepsilon > 1$$

STEP 3: Compute the parameter $vol(A_g(\varepsilon))$ according to the following equation:

$$vol(A_g(\varepsilon)) = \sum_{m_1=0}^{M_1-1} \sum_{m_2=0}^{M_2-1} U_{\varepsilon}(m_1, m_2) - L_{\varepsilon}(m_1, m_2) \quad (5)$$

STEP 4: The Minkowski - Bouligand dimension is obtained by the relation:

$$D_{MB} = 3 - \alpha \quad (6)$$

where α is the slope of the best fitting line at the points $(\ln \varepsilon, \ln vol(A_g(\varepsilon)))$, for $\varepsilon = 1, 2, \dots, \varepsilon_{max}$.

The k th-Nearest Neighbour estimator (K-NN)

In a previous work [9], an algorithm for calculating the fractal dimension of grey level images using the k th-nearest neighbour approach was presented. In this work, a slightly modified method is applied for the estimation of the fractal dimension.

In particular, let $I(x, y)$ denotes a grey level image with size $N_x \times N_y$ pixels, then the fractal dimension is estimated iteratively, using the following equation:

$$\langle r_k^\gamma \rangle \sim (k/N)^{\gamma/D(\gamma)} \quad (7)$$

for $k = k_{min}, \dots, k_{max}$ (k integer), where $\langle r_k \rangle$ is the scaling of the average distance of a point to its k th nearest neighbour as a function of k , N the number of points, and $D(\gamma)$ the dimension function. The fractal dimension is then estimated as follows:

STEP 1: An initial value of γ , $\gamma_0 = 2.5$, is chosen arbitrarily.

STEP 2: Each pixel of the image with spatial coordinates (x, y) is considered as a point of R^3 with coordinates $(x, y, I(x, y))$. For each such point, which will be referred as a reference point, its k_{min} up to k_{max} nearest neighbours are recorded as r_{k_m} ($m = 1, 2, \dots, N$), where $N = N_x \times N_y$ denotes the total number of the pixels in the image.

STEP 3: For $n = 1, 2, \dots$ the following recursive relations:

$$D(\gamma_n) = \frac{\gamma_{n-1}}{s_{n-1}}, \gamma_n = D(\gamma_n) \quad (8)$$

are applied until convergence is achieved. s_{n-1} is the slope of the best fitting line (using linear regression) at the points

$(\log(k/N), \log \langle r_k^{\gamma_{n-1}} \rangle)$ and $\langle r_k^{\gamma_{n-1}} \rangle = \frac{1}{N} \sum_{m=1}^N r_{k_m}^{\gamma_{n-1}}$. The

distance between two points is determined using the Euclidean norm. The process can be terminated when the fractional range between γ_{n-1} and $D(\gamma_n)$,

$\left| \frac{D(\gamma_n) - \gamma_{n-1}}{0.5[D(\gamma_n) + \gamma_{n-1}]} \right|$, is smaller than some predefined tolerance (e.g., 10^{-5}).

III RESULTS

The data used in the present study are composed of rectangular ROIs of:

- Normal parenchyma: 99 ROIs.
- Hepatocellular carcinomas: 50 ROIs.

In Fig. 1, two typical CT liver images with or without hepatic lesions are presented. The rectangular areas correspond to the best fitting rectangular, within the ROIs, as drawn by the experts, where the fractal dimension is estimated using the aforementioned methods.

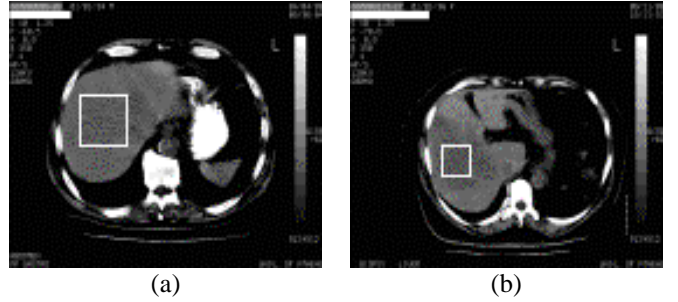


Fig. 1. Typical transverse CT slices of (a) normal liver parenchyma and (b) hepatocellular carcinomas. The rectangular areas represent the ROIs under study.

In Table I, the mean and the standard deviation values of the fractal dimensions, using the four aforementioned fractal dimension estimators, and for each hepatic case, are then presented.

TABLE I
THE MEAN AND THE STANDARD DEVIATION (IN PARENTHESIS)
OF THE FRACTAL DIMENSIONS FOR ALL ROIs AND FOR EACH
HEPATIC LESION.

	PSM	BCM	MFE	K-NN
Normal	2.25 (0.47)*	2.18 (0.09)	2.86 (0.06)	2.26 (0.07)
Hepatocellular carcinomas	2.85 (0.17)*	2.14 (0.15)	2.86 (0.06)	2.04 (0.11)

*The values (mean, standard deviation) of the fractal dimension for the PSM method were calculated for a substantial number of the original data (normal parenchyma: 57 and hepatic carcinoma: 46) since the method underestimates the estimation of the fractal dimension for most of the liver ROIs.

For the estimation of the PSM, the range of the values of the parameter k , over which the slope of the best fitting line is computed, was [15,20]. Additionally, the ranges of the values of the parameter k used for the estimation of the BCM, MFE and K-NN were [7,19], [3,15] and [50,150], respectively. It must be pointed out that these ranges were

finally selected as the optimum ones in relation to the fractal dimensions estimated by the methods.

From Table I, it can be observed that the K-NN may provide an indication of the type of the hepatic lesion under study, based on its fractal dimension. The values of the fractal dimension using the other two methods, BCM and MFE, are quite similar and they could not provide any information for the discrimination of these specific hepatic lesion. Nevertheless, the PSM method can not provide any discrimination between the two categories since the fractal dimensions obtained are above the value of 3; thus ROIs have been eliminated from the study. For these reasons, a discriminant analysis is then performed.

Furthermore, a well-known algorithm namely the Fuzzy C-Means algorithm [10] was then applied for the clustering of the input data into two clusters. The FCM algorithm minimises the sum of squared distances to the prototypes weighted by constrained membership that can be interpreted as degrees of sharing. The function has two arguments. The first is a feature vector, which is formed by all the values of the fractal dimension, to be classified into two clusters. The number of clusters, which is the second argument, corresponds to the normal parenchyma and the hepatocellular carcinoma, respectively. It returns the cluster number for which the pattern vector has the highest grade. The FCM clustering for each hepatic lesion and for each fractal dimension estimator is then presented in Table II.

TABLE II
FCM CLUSTERING FOR EACH HEPATIC LESION AND FOR EACH FRACTAL DIMENSION ESTIMATOR

Clusters	BCM		MFE		K-NN	
	Normal	HCC	Normal	HCC	Normal	HCC
Cluster I	48/99	17/50	72/99	37/50	92/99	9/50
Cluster II	51/99	33/50	27/99	13/50	7/99	41/50
Success rate	48.48%	66.00%	72.73%	26.00%	92.93%	82.00%

From the results of the Table II, it is obvious that the k-th nearest neighbour (K-NN) outperforms the BCM and the MFE methods. Specifically, the K-NN method discriminates almost 93% of the normal parenchyma (92 out of 99 normal parenchyma) and 82% of the hepatocellular carcinoma (41 out of 50 hepatocellular carcinoma) correctly to the two clusters. Therefore, the K-NN method may be used to discriminate the normal parenchyma from the hepatocellular carcinoma using CT liver images

V. CONCLUSION

In this paper, a comparative study is performed to discriminate two different CT liver lesions: normal parenchyma and hepatocellular carcinoma. The fractal dimension of 99 ROIs of normal images and of 50 ROIs of hepatocellular carcinoma had been computed throughout four different estimators, regarded as the most representative: the Power Spectrum Method (PSM), the

Box-Counting Method (BCM), the Morphological Fractal Estimator (MFE), and the kth-Nearest Neighbour estimator (K-NN), as a novel implemented method. The results of the discriminate analysis show that the K-NN could discriminate the two liver lesions more efficiently than the BCM and MFE methods. In particular, the PSM was proved to be insufficient for the current study, since underestimates the fractal dimension of most of the CT data. The success rate of discrimination with the K-NN method reached 93% for the normal parenchyma and 82% for the hepatocellular carcinoma. In the future, the proposed method might be used for the extensive analysis of other liver lesions or organs towards to the classification problem.

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